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AGRICULTURAL PRODUCTIVITY AND RURAL HOUSEHOLD INCOMES: MICRO-LEVEL EVIDENCE FROM ZAMBIA

By

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ABSTRACT

It is widely accepted that agricultural productivity growth generates important multiplier effects on the rest of the economy through indirect linkages. However, most of this evidence comes from Asia and Latin America. Micro-level evidence in support of this hypothesis in Sub-Saharan Africa is actually quite thin. This study estimates a reduced form relationship between multi-year lagged district-level summaries of crop productivity and total, own-farm, and off-farm income in Zambia. We use nationally representative household survey data to analyze this relationship; the nature of these data is unique to Zambia. Findings show a strong link between district-level productivity and household own-farm income. A doubling of multi-year lagged median district crop productivity per hectare translates into a 25-33% increase in own-farm income after controlling for household and community factors. There is some evidence of a positive link between district-level productivity and total household income, but the relationship between district crop productivity and off-farm income is sensitive to the model specification and imprecisely measured, suggesting that some of the critiques of the multiplier hypothesis for contemporary Africa may be valid. However, when the lagged crop productivity measures are confined to small farms cultivating less than 2 hectares, we find some evidence of a positive contribution of increases in lagged district-level productivity to off-farm income – a doubling of productivity leading to a 34% increase in off-farm income.

Key words: Agricultural productivity, rural incomes, Zambia.

JEL codes: Q12, Q18.

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ACRONYMS

AE	Adult Equivalent
AIC	Akaike Information Criterion
CFS	Crop Forecast Survey
CRE	Correlated Random Effect
CSO	Central Statistical Office
CV	Coefficient of Variation
FISP	Farmer Input Support Programme
FRA	Food Reserve Agency
IAPRI	Indaba Agricultural Policy Research Institute
IFAD	International Fund for Agricultural Development
MoA	Ministry of Agriculture
OLS	Ordinary Least Squares
RALS	Rural Agricultural Livelihoods Survey
TAMSAT	Tropical Applications of Meteorology using Satellite Data and Ground-based Observations
TLU	Tropical Livestock Unit
ZMW	Zambian Kwacha

1. INTRODUCTION

It is widely agreed that in early-stage developing economies, agricultural growth is almost always at the heart of initial structural transformation processes. Based on the early development economics literature dating back to Lewis (1954), Ranis and Fei (1961), and Johnston and Mellor (1961), it has become a stylized fact that agricultural productivity growth generates important general equilibrium effects on the rest of the economy through linkages with other production sectors, factors markets, downstream agricultural marketing systems, and consumption (Hirschman 1958; Mellor 1976; Hirschman 1992; Block and Timmer 1994; Haggblade, Hazell, and Reardon 2007; Barrett, Carter, and Timmer 2010). A major conclusion from this literature is that policies that discriminate against agriculture can hamper structural transformation and economic growth (Dennis and İşcan 2011).

The empirical literature suggests that the total economy-wide multiplier effect of agricultural growth is greater than one, i.e., that the additional value of output generated outside of agriculture is greater than the initial additional value of agricultural output. Agricultural growth multiplier effects have been estimated to be in the range of 1.6 to 1.8 in Asia and 1.3 to 1.5 in Africa and Latin America (Haggblade, Hazell, and Reardon 2007).

However, almost all of the estimated multiplier effects in the literature come from modeling based on input-output and social accounting matrix models (Subramanian and Sadoulet 1990; Vogel 1994), semi-input-output and mixed models (Parikh and Thorbecke 1996; Dorosh, Niazi, and Nazli 2003), and computable general equilibrium models (Bigsten and Collier 1995; De Janvry and Sadoulet 2002). While these approaches have provided important and useful estimates of the contribution of agricultural growth to growth in other sectors of the economy, their main shortcomings are that model parameters – and hence outcomes and conclusions – are typically based on informed assumptions about key behavioral effects (e.g., elasticities) rather than being estimated from actual micro-level data. This is understandable because of the historic paucity of suitable micro-level data to estimate these effects in most developing countries. Christiaensen, Demery, and Kuhl (2011) note that the validity of these models depends on the accuracy of structural assumptions, which may quickly become outdated in rapidly evolving economies such as those in most of Africa today (Barrett et al. 2017; Jayne, Chamberlin, and Benfica 2018). There has also been some recent skepticism that agriculture can serve as the primary engine of growth for broader economic development in Sub-Saharan Africa (Ellis 2005; Collier and Dercon 2014; Dercon and Gollin 2014)

The micro-level evidence underpinning the Johnston-Mellor agricultural growth multipliers hypothesis for contemporary Africa is surprisingly weak considering that it continues to be the foundational framework for most agricultural economists' view of the development process in this region. In fact, we are unaware of any African micro-level studies that estimate the impact of agricultural productivity growth - which may have complex lagged effects - on household incomes or consumption. This is largely because of the unavailability of annual household or regional data on agricultural productivity over a reasonably long time period.

This study identifies the effects of changes in agricultural productivity on the incomes per adult equivalent for households surveyed in two waves, 2012 and 2015, of the nationally representative Rural Agricultural Livelihoods Survey (RALS) in Zambia. We merge these two waves of data with multiple lags of district-level crop productivity measures computed from Zambia's annual Crop Forecast Surveys (CFSs). The CFSs are representative at the district level. Lag length is up to a potential of 6 years, with the number of lags determined by model selection criteria. This approach allows us to estimate the strength of the relationship between district-level lagged values of crop land productivity and rural farm household incomes from own-farm and off-farm work. We also investigate the robustness of these relationships to alternative lag structures of district-level productivity, the use of alternative district summaries of productivity, such as the median, mean, 10th and 90th percentiles, and alternative sub-samples of farms to examine whether the productivity changes of small farms matter more than relatively larger farms.

Our reduced form model specification has similarities to those used by Bautista (1990), Bravo-Ortega and Lederman (2005), Tiffin and Irz (2006), and Christiaensen, Demery, and Kuhl (2011), and Ligon and Sadoulet (2018). However, unlike these studies, which rely on cross-country national-level data, our study identifies the effects of agricultural productivity on rural household incomes using household-level panel data merged with annual statistically representative district-level data on agricultural productivity over multiple consecutive years in Zambia. There are three advantages of this approach. First, we can identify the potentially complex lagged effects of agricultural productivity at fairly localized spatial levels and examine the robustness of the results to alternative summary measures of productivity. Empirical estimates such as these have important policy implications in light of growing speculation that the multiplier effects of agricultural growth on the rest of the economy may be weakening in Africa as the continent transforms and diversifies always from agriculture (see Diao et al. 2012 for a useful review) or might have been over-emphasized all along (e.g., Dercon and Gollin 2014). Second, we can isolate the effects of agricultural productivity on household incomes from own-farm and off-farm sources. Third, we can estimate these relationships after controlling for household- and community-level factors that may be correlated with agricultural productivity, which are generally unavailable at national level and hence cannot be included in cross-country analyses. The study therefore contributes to the empirical literature on agricultural growth effects in developing countries by providing a relatively current and much needed micro-level foundation to the topic.

The remaining sections of the article update the conceptual underpinnings of the farm-off-farm multiplier/growth linkages literature in light of recent structural developments in rural Africa, present the empirical model, data, and estimation strategy, discuss the results, summarize the main findings and contributions of the study, and speculate on policy directions for encouraging inclusive forms of economic transformation. In general, the study upholds a robust positive association between district-level agricultural productivity and own-farm household income, and a less robust but still positive association between this productivity and total household income. There is also some evidence of a positive association between the productivity levels of smaller farms in the district and rural off-farm household income.

2. ANALYTICAL FRAMEWORK

In this section we discuss the conception underpinnings and empirical model.

2.1 Conceptual Underpinnings

The agricultural sectors of most developing areas are extensively connected to the wider economy through production, consumption, factor market, and wage good linkages (Hirschman 1958; Mellor and Lele 1973; Hirschman 1992; Block and Timmer 1994; Haggblade, Hazell, and Reardon 2007; Barrett, Carter, and Timmer 2010). Production linkages arise when increased agricultural output stimulates the demand for goods and services provided by firms in off-farm stages of agrifood systems, including input suppliers, providers of farm technical services, food processors, wholesalers, retailers, etc. Consumption linkages arise from increased farmer income due to productivity growth, which boosts their expenditures and hence the demand for goods and services in the local economy. Haggblade, Hazell, and Reardon (2007) reports from a highly reported study in Malaysia that consumption linkages may account for up to 80% of the total indirect income gains resulting from agricultural growth. Factor market linkages arise as labor in agriculture becomes more productive, allowing it to be released into off-farm sectors, or as production surpluses finance investments in off-farm activities. Finally, wage good linkages arise as agricultural growth boosts the supply of food, thereby lowering prices for consumers and increasing their real wages.

Notwithstanding the longstanding acceptance of these stylized facts, Sub-Saharan Africa's labor force has shifted substantially since 2000, with a declining share of the labor force working on farms and a rapidly rising share in off-farm and downstream agrifood system jobs (Yeboah and Jayne 2018; IFAD 2019), and with projections continuing to point in this direction over the next 15-30 years (Tschirley et al. 2015). This has led to speculation that the dynamic sectors of African economies may be changing and that the role of agricultural growth, while still important, may be weakening over time as Africa's economies become more diversified. Still others, such as Collier and Dercon (2014) contend that smallholder agriculture in most African countries was too constrained to ever allow it to be a dynamic engine of growth. Ultimately, the strength and significance of agricultural productivity change on rural farm and off-farm incomes is an empirical question.

In measuring the relationship between agricultural productivity in a localized area and the incomes of households in that area, a number of identification issues must be addressed. These include:

2.1.1 Causality

In a critique of previous empirical analyses on the role of agriculture in economic growth, Tsakok and Gardner (2007) argue that most early studies using cross-sectional data for a panel of countries have been limited by inability to distinguish between correlation and causality, as the relationship between off-farm income growth and agricultural growth most likely moves in both directions (Mellor and Johnston 1984). We therefore need an identification strategy that convincingly isolates the influence of localized agricultural productivity change on the income levels of households in the surrounding area.

2.1.2 Omitted Effects

Tsakok and Gardner (2007) also highlight the role of unobserved factors, which cannot be adequately controlled for in analyses using low frequency and highly aggregated national-level data. Thanks to the growing availability of household panel survey data, it may be possible to control for unobserved household effects as well as observed household and community covariates, when measuring the relationship between localized agricultural growth indicators and household incomes.

2.1.3 Dynamic Effects

Certainly the multiplier effects of agricultural productivity growth do not occur within one year; lagged effects are likely to be important (Tsakok and Gardner 2007).

These identification challenges are addressed in the following empirical model.

2.2 Empirical Model

Our starting point to identify the effects of lagged district-level crop land productivity on smallholder household incomes per adult equivalent (AE) is the following general empirical model:

$$y^I_{idpt} = \beta_0 + \sum_{j=1}^{J} y^A_{dp,t-j}\beta_1^{t-j} + x_{idpt}\beta_2 + z_{idpt}\beta_3 + s_{idpt}\beta_4 + \beta_5 d_{dpt} + r_{idpt}\beta_6 + c_i + \lambda_t + \theta_p + \omega_{p,t} + v_{idpt} \qquad 1$$

where $i, d, p,$ and t index the household, district, province, and year, respectively;[1] j indexes the lag; *J* is the total number of lags; $y^I_{i,t}$ represents total or sectoral household income per adult equivalent (income/AE) ; $y^A_{dp,t-j}$ for *j=1, 2, …, J* represents district-level summaries of the value of lagged crop productivity per hectare (described in more detail below). The β_1^{t-j}'s are the main parameters of interest. The control variables are defined as follows: $\boldsymbol{x_{idpt}}$ is a vector of household demographic characteristics, including the number of adult equivalents in the household, the education of the household head, and an indicator variable for female-headed households; $\boldsymbol{z_{idpt}}$ is a vector of quasi-fixed factors, including the household's landholding size in hectares, tropical livestock units (TLU) owned, and value of farm equipment; $\boldsymbol{s_{idpt}}$ is a set of household variables indicating accessibility to infrastructure services, including distance to the nearest district town, tarmac road, feeder road, marketplace, and agro-dealer; d_{dpt} is a district-level measure of cell phone density (number of cell phones per adult equivalent in the district) to capture fairly localized time-varying effects associated with advances in communications and information flows that might influence crop productivity.

We also control for multiple rainfall variables, represented by the vector $\boldsymbol{r_{idpt}}$. The first is total rainfall during the most recent growing season (November-March), which would directly affect farm income in year *t*. Second, we include long-run average growing season rainfall (defined as a moving average of growing season rainfall during the 16 years prior to the current growing season) to control for long-term productivity potential. Third, we control for moisture stress during the most recent growing season, defined as the number of overlapping 20-day periods with less than 40 mm

1 Districts are sub-divisions of provinces.

of total rainfall, as well as the long-run average number of moisture stress periods (16 year moving average). The moisture stress variables are meant to account for the fact that, below a threshold level of rainfall within a certain period, productivity may decline dramatically for the season even though the total rainfall over the course of the season may be similar to other seasons. Finally, we include the coefficient of variation (CV) of growing season rainfall over the 16 growing seasons prior to year *t*, meant to control for spatial differences in the variability of rainfall.

All of the variables in $\boldsymbol{x}$, $\boldsymbol{z}$, $\boldsymbol{s}$, *d*, and $\boldsymbol{r}$ are considered predetermined. Finally, c_i is time-constant unobserved household-level heterogeneity; λ_t is a year fixed effect; θ_p denotes province fixed effects; $\omega_{p,t}$ denotes province-by-year fixed effects; and v_{idpt} is the idiosyncratic error term.

3. ESTIMATION STRATEGY

The general hypothesis is that there is a relationship between long-term district-level agricultural land productivity and the total, own-farm, and off-farm incomes/AE of rural households in that district. We are, therefore, mainly interested in deriving unbiased estimates of the β_1^{t-j}'s. We also want to determine whether changes in agricultural productivity have a greater impact on own-farm or off-farm incomes. To estimate equation (1) and test this hypothesis, we employ a correlated random effects (CRE) Mundlak-Chamberlain device (Mundlak 1978; Chamberlain 1984), distributed lag approach. In particular, we include both the levels and household time-averages of the $\boldsymbol{x}$, $\boldsymbol{z}$, $\boldsymbol{a}$, d, and $\boldsymbol{r}$ control variables but only the levels (and not the time-averages) of the lagged district summary measures of crop productivity. Including the household time-averages of the former leverages the panel structure of the data to control for time-constant unobserved heterogeneity (c_i) that may be correlated with the observed covariate controls (i.e., it does not require c_i to be independent of these covariates). Excluding the time averages from the lagged variables allows us to avoid some of the transitory noise and attenuation bias that may accompany differencing (or demeaning) overlapping lags of district crop productivity as would be the case in a standard fixed effects model. McKinnish (2008) discusses how "instruments that are lagged several periods behind the independent variable and instruments that are differences of lagged observations will tend to be particularly weak". While we are not using lagged instruments, we are using overlapping lagged independent variables, and the same logic should apply. We expect that by differencing (or demeaning or taking the time averages) these overlapping lagged variables we would be left with a lot of transitory noise and attenuation bias.

We estimate equation (1) for different measures of household income/AE (namely, total income and then its constituent parts: own-farm income, and off-farm income sources. Estimates from these models will enable us to identify the pathways through which lagged district-level farm productivity measures affect sectoral household income.

To determine whether our results are robust to alternative plausible measures of agricultural productivity, we define multiple district-level productivity measures from the CFS and report how their coefficient estimates compare. It is unlikely that any single district summary measure of crop productivity is sufficient to capture its impact on smallholder household income/AE. The multiplier effect from aggregate crop productivity to household income might be substantially different if the main transmission channel is already highly productive farmers compared to low productivity farmers, or on larger farms compared to smaller ones. By examining how the impacts of these different distributional measures vary, we can get a better understanding of the nature of the multiplier effect of crop productivity on sectoral incomes. The specific district summary measures of the value of crop output productivity that we estimate include the overall median and mean, the 10th and 90th percentiles (estimated together in the same model), and the median for farms with less than two hectares planted and greater than or equal to two hectares planted, respectively (also estimated in the same model).[2] In the construction of these district summary measures, we divide the numerator and the denominator of the respective productivity measures after summarizing each

[2] The Zambia Ministry of Agriculture considers farms under 5 hectares cultivated to be small-scale farms. Farms cultivating between 5 and 20 hectares are considered medium-scale farms, while farms over 20 hectares are considered large-scale.

element individually by district. This gives an implicit weighting of the productivity measures according to the output values and areas planted for specific types of farm households.

Finally, we account for longer-run effects of district-level crop productivity on household incomes by: (a) including multiple lags of the respective crop productivity variables, or (b) including a moving average of the respective lagged crop productivity variables. For (a), including multiple lags in an unrestricted form may create problems with multicollinearity (e.g., if y^a_{dpt-1} is strongly correlated with y^a_{dpt-2} and y^a_{dpt-3}, etc.). For this reason, we estimate a quadratically distributed lag model (also known as an Almon lag (Almon 1965)), which provides both flexibility and parsimony in the distribution of the lag structure. The flexibility of the distribution allows us to consider the possibility that the impact of crop productivity may not reach its highest point after a single year but may instead rise over multiple years before declining. For example, the multiplier effects from rising crop productivity likely take more than one year to materialize and might even be negative in certain years. To operationalize the Almon lag approach, we assume that β^j_1 in equation (1) can be approximated by a second degree polynomial, i.e., $\beta^{t-j}_1 = \alpha_0 + \alpha_1 j + \alpha_2 j^2$ for *j* = 0, 1, 2, …, *J-1*[3] and where the α's are parameters to be estimated. The estimated β^{j-1}_1's are then calculated from the estimated α's. We determine the optimal lag length (*J*) by selecting the *J* that minimizes the Akaike information criterion (AIC) in each model (per guidance in Pindyck and Rubinfeld 1997 and Gujarati 2003). However, we set a minimum lag length of three lags. We implement the Almon lag approach in a level-level specification (i.e., a specification in which both the dependent variable and lagged productivity variables are in levels, not logs). Unfortunately, implementing the Almon lag approach in a log-log specification would be problematic because recovering the β^{t-j}_1's would entail adding together logged parameters, the result of which is not equivalent to logging the β^{t-j}_1's. For (b), the moving average models, we use the same maximum lag length as determined in (a) using the AIC criterion, and we estimate (b) using both level-level (as a direct comparison to (a)) and log-log specifications.[4]For all of the level-level models, we use the recovered β^{t-j}_1s to derive elasticities on the lagged and/or multi-year productivity variables.

Our estimation strategy takes steps to effectively address the three potential threats to internal validity mentioned above, i.e., causality, omitted effects, and misspecified dynamic effects. First, unlike many of the earlier studies that relied on cross-sectional data, we make use of multiple years of district productivity data, derived from separate datasets, to evaluate the lagged and dynamic nature of impact that area productivity has on household incomes. Second, many studies in Africa rely mainly on national or regional level data, making it difficult to control for household or even community level effects. We have access to highly detailed household level panel data – something which hasn't been available in the past – to control for both time invariant unobserved heterogeneity, and time variant highly localized heterogeneity, including household assets, rainfall

[3] The Almon lag formula assumes that you are starting at time lag zero (i.e., the current period), corresponding to *J* = 0. Since we start at time lag one, for the purpose of implementing the Almon lag formula we designate *J* = 0 to be time lag one, J = 1 to be time lag two, and J-1 to be the final lag.

[4] In the log-log specifications we only log the moving average lagged productivity variable of interest, while keeping the control variables as levels (many of which have numerous zero values). Elasticities are calculated for the controls after the estimation using mean variable values.

indicators, distance to key infrastructure services, and district level cell phone density. Changes in Zambia Food Reserve Agency (FRA) and the Farmer Input Support Programme (FISP) operations are also very important time-varying effects, but we believe that they influence total income mainly through how they influence lagged district productivity, which we are testing for.[5]

[5] The FRA is a strategic food reserve/maize marketing board that buys maize from farmers at a pan-territorial price at its depots throughout the country. This price often (but not always) exceeds the market price of maize in areas that produce a maize surplus. FISP is Zambia's agricultural input subsidy program.

4. DATA

The data used for this analysis come from three main sources. The dependent variables — household incomes from own farm and off-farm work, and the sum of these (total household income) — and all the control variables in $\boldsymbol{x}$, $\boldsymbol{z}$, $\boldsymbol{a}$, and $\boldsymbol{d}$ (see below) come from the Rural Agricultural Livelihoods Survey (RALS), a two-wave panel survey covering the 2010/11 and 2013/14 agricultural years (October-September) and the subsequent marketing years (May-April of 2011/12 and 2014/15, respectively). The RALS data were collected in June-July 2012 and 2015 by the Indaba Agricultural Policy Research Institute (IAPRI) in collaboration with the Zambia Central Statistical Office (CSO) and Ministry of Agriculture (MoA). This is a nationally representative survey of smallholder farm households[6] with a two-stage, probability proportionate to size sample design. The first stage is stratified by district with standard enumeration areas (clusters) identified as the primary sampling unit. The second stage is stratified by household category, with households grouped into three categories based on area cultivated, number of livestock raised, and specialty crops produced, with households within each stratum designated as the secondary sampling unit. See CSO (2012) for additional details on the household categories and CSO et al. (2012) for additional details on the survey and sampling design.

In total, there were 8,839 households surveyed in the RALS 2012 survey, of which 7,254 (82%) were successfully re-interviewed in the RALS 2015 survey. We use the regression-based approach recommended by Wooldridge (2010) to test for attrition bias in each of our main final models.[7] We discuss these test results and their implications for interpretation of our main econometric estimates near the end of the Results section.

The income data is generated from the 2011/12 and 2014/15 marketing years. It is calculated by summing up (a) gross own farm income (including value of crops, fruits, and vegetables harvested, income from live and slaughtered animals, value of slaughtered animals for home consumption, and value of livestock production, including of milk, eggs, broilers, and fish products), and (b) gross off-farm income (total in-kind and cash income from all activities except for own-farm, including salary or wage employment and gross household income from informal business activities from both inside and outside the agri-food system, remittances in the form of cash, maize, or other commodities received, the value of wild products collected, and the value of charcoal produced for home use). This sum of these two components equals (c) total household income. All three income measures are divided by the number of adult equivalents (AE) in the households.

Table 1 (following) shows the farm size distribution (in terms of hectares cultivated) of the population that our final RALS sample represents. While the majority of households in both years cultivated less than two hectares of land, the farm size distribution overall shifted upwards in 2015.

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[6] Not all of the RALS households in the data had access to land and own-farm income for both years. We included in our estimation all households that had own-farm income and/or access to land for at least one of the years in the panel.

[7] This involves creating a dummy variable (sit+1) equal to 1 if the household was interviewed in both waves of the panel, and equal to 0 if it was only interviewed in the first wave, and then estimating equation (1) via ordinary least squares (OLS) for each dependent variable using all of the observations from the first wave and including sit+1 as an additional covariate. The null hypothesis is that the parameter associated with sit+1 equals zero – i.e., that there is no attrition bias in the sense of systematic differences in the dependent variable after controlling for the observed covariates.

Table 1. Hectares (X) Cultivated by Sampled Population – Percentage by Size Category

Year	0<X<2	2<=X<5	5<=X<10	X>10
2012	71%	25%	4%	1%
2015	62%	32%	6%	1%

In 2012, 71% of households cultivated less than two hectares and 25% cultivated two to five hectares, while in 2015, only 62% of household cultivated less than two hectares but 32% cultivated two to five hectares.

The district summaries of lagged household values of crop productivity come from the annual Zambia CFS conducted by CSO and MoA. These data, which we include potentially since the 2004/2005 agricultural season (a maximum of six lags) and are collected in late March/early April shortly before the main harvest period begins in May, are based on farmers' expected quantity harvested of each crop.

The CFSs are statistically representative of smallholder farm households at the district and national levels. The samples for these surveys are also based on a probability proportional to size schema. Sample sizes each year range from 8,018 to 13,515 smallholder farm households. This enables us to compute statistically representative estimates of crop output per hectare harvested for each year for each of Zambia's 72 districts that were represented in the data.[8]

The final productivity variables are calculated by: (a) summing up the estimated gross value of field crops harvested[9] for each household in each district, based on constant 2016 prices per kilogram in the data; [10] (b) calculating the district-level summary measures of this value -- including median, mean, 10th and 90th percentiles, and median for farms less than two hectares planted and greater than or equal to two hectares planted, respectively, (c) calculating the same district summary measures for the number of hectares planted, and then (d) dividing (b) by (c) for each district to get the weighted summary measure of value of field crops harvested per hectare planted.

The rainfall measures are calculated from data collected by Tropical Applications of Meteorology using Satellite data and ground-based observations (TAMSAT) (Tarnavsky et al. 2014; Maidment et al. 2014; Maidment et al. 2017). We use dekadal (10-day) data for moisture stress periods and monthly data for the other rainfall measures. The TAMSAT data were matched to the GPS locations of the RALS households and the rainfall indicators were derived using the Raster Calculator tool in ArcGIS Model Builder. The TAMSAT data has a spatial resolution of approximately 0.0375 x 0.0375 degrees, which is roughly 4 x 4 kilometers, or 16 square kilometers, and so for all practical purposes they can be thought of as village-level measures. See Table 2 for summary statistics for the various dependent, explanatory, and related variables by RALS year.

[8] Starting in 2010/2011 two additional districts were created. However, to be consistent with the earlier years, we assigned them to the same districts that they were apart of previously

[9] The field crops reported in the CFS are maize, cassava, sorghum, rice, millet, sunflower, groundnuts, soyabeans, seed cotton, Irish potatoes, Virginia tobacco, burley tobacco, mixed beans, bambara nuts, cowpeas, velvet beans, coffee, sweet potatoes, paprika, pineapple, popcorn, and sugar cane.

[10] If data was available and sufficient, we applied the district median price for each crop to all households, else we used other price estimation approaches.

Table 2. Summary Statistics for Each RALS Year – Mean and 25th, 50th, and 75th Percentiles

Year	2012				2015			
Summary measure	Mean	25pct	50pct	75pct	Mean	25pct	50pct	75pct
Gross total income/adult equivalent (AE) in constant 2016 ZMW	4,823	1,359	2,489	4,687	5,054	1,297	2,449	4,877
Gross off-farm income/AE (2016 ZMW)	2,480	188	548	1,712	3,040	260	763	2,300
Gross own-farm income/AE (2016 ZMW)	2,343	677	1,382	2,583	2,014	534	1,176	2,287
Key explanatory variables								
Median district crop output (2016 ZMW)/hectare – Lag 1	3,018	2,391	2,875	3,471	3,928	2,228	3,164	5,500
(…) – Lag 2	3,824	2,387	3,483	5,454	3,721	2,251	2,828	5,207
(…) – Lag 3	3,464	1,121	3,151	5,325	3,939	2,685	3,388	4,665
(…) – Lag 4	2,152	1,270	1,801	2,828	3,018	2,391	2,875	3,471
(…) – Lag 5	3,346	1,493	1,747	5,000	3,824	2,387	3,483	5,454
(…) – Lag 6	3,975	831	1,732	6,044	3,464	1,121	3,151	5,325
Control variables								
Household adult equivalents	4.5	2.9	4.3	5.8	4.8	3.2	4.6	6.1
Years of household head education	5.8	3.0	6.0	8.0	5.7	3.0	6.0	8.0
Female headed household (=1)	0.2	0.0	0.0	0.0	0.3	0.0	0.0	1.0
Total land holding size (ha)	2.9	0.9	1.8	3.2	4.1	1.0	2.1	4.3
Tropical livestock units (TLUs)	2.3	0.0	0.0	2.0	2.5	0.0	0.0	2.2
Value of farm equipment (2016 ZMW)	13,090	835	1,943	5,105	15,868	943	2,279	7,269
Growing season (GS) rainfall (mm)	794	722	793	859	849	782	827	912
16-year average of prior GS rainfall (mm)	798	744	813	850	810	753	821	869
GS number of rainfall stress periods (SP)	0.7	0.0	1.0	1.0	1.4	0.0	1.0	2.0
16-year average of prior GS rainfall SP	1.0	0.6	1.1	1.4	0.8	0.4	0.9	1.2
CV of rainfall over previous 16 GS	13.0	10.1	12.7	14.9	11.0	8.7	10.8	12.5
Number of cell phones/AE	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.3
Distance to nearest district town (km)	42.1	18.0	35.0	60.0	40.1	17.0	34.0	55.0
Distance to nearest paved road (km)	32.2	5.0	19.0	45.0	29.2	4.0	15.0	42.0
Distance to nearest feeder road (km)	2.0	0.0	0.0	1.0	2.0	0.0	0.0	1.0
Distance to nearest market (km)	26.3	5.0	15.0	35.0	24.5	5.0	14.5	35.0
Distance to nearest agro-dealer (km)	32.2	10.0	24.0	45.0	30.8	8.0	21.0	40.0

Notes: N = 14,464

5. RESULTS

In this section we present the results of the effects of multi-year lagged productivity on incomes, using multiple specifications (incorporating 3-6 lags, depending on the model selection criteria). Table 3 presents the elasticities for each type of income, based on level-level Almon multi-year lag models for lagged district median productivity. Table 4 presents similar results to Table 3 but for the log-log lagged moving average specification. The lagged multi-year effects reported in Table 3 are the elasticities of the sum of the individual lagged level effects (before elasticities are calculated for the individual lags), which are recovered from the estimated Almon lag α's. There are several core results.

Table 3. Effects (Reported as Elasticities) of Multi-Year Lagged Median District Crop Productivity on Household Incomes (I) per Adult Equivalent AE – Level-Level with Almon Lag (2016 ZMW)

	Total I/AE		Off-farm I/AE		Own-farm I/AE	
	Elasticity	*P*-value	Elasticity	*P*-value	Elasticity	*P*-value
District median lag 1	-0.210	0.147	-0.472*	0.068	0.222	0.168
District median lag 2	0.460	0.098	0.649	0.187	0.176**	0.010
District median lag 3	-0.086	0.357	-0.115	0.443	0.102***	0.003
District median lag 4	--	--	--	--	0.019	0.617
District median lag 5	--	--	--	--	-0.051	0.289
District median lag 6	--	--	--	--	-0.139***	0.001
District median long-run	0.139	0.261	0.018	0.927	0.326**	0.012
Adult equivalents	-0.935***	0.000	-0.878***	0.000	-1.014***	0.000
Education of the HH head	0.044	0.565	0.066	0.535	0.017	0.839
Female head (=1) (coef.)	-1675	0.110	-1608	0.112	-67.17	0.753
Landholding size (ha)	0.008	0.707	-0.009	0.798	0.028	0.291
Tropical livestock units	0.155**	0.018	0.116*	0.084	0.205***	0.003
Value farm equipment	0.083	0.159	0.124	0.202	0.031	0.312
GS rainfall	0.590	0.316	1.024	0.269	0.130	0.777
16 year mean rainfall	0.276	0.894	-0.273	0.930	0.796	0.702
Rainfall stress periods (SP)	0.044	0.440	0.018	0.813	0.074	0.323
16 year mean rainfall SP	-0.238	0.491	-0.101	0.748	-0.479	0.475
16 year rainfall CV	0.834	0.148	0.776	0.357	1.132	0.195
Cell phone density	-0.077	0.838	-0.587	0.346	0.443	0.218
Distance to district town	0.164	0.141	0.054	0.426	0.308	0.214
Distance to paved road	-0.003	0.934	0.032	0.322	-0.054	0.501
Distance to feeder road	0.000	0.962	0.003	0.590	-0.003	0.288
Distance to market	-0.047	0.267	-0.020	0.426	-0.077	0.386
Distance to agro-dealer	-0.100	0.139	-0.101*	0.088	-0.097	0.438
Year (2015 = 1) (coef.)	1163	0.378	1827	0.103	-338	0.545

Note for Table 3: 14,464 observations in each model. Province dummies and province*year interaction effects included in all of the models, but not reported. Household time-averages of control variables included for CRE but not reported. Triple asterisk (***), double asterisk (**), and single asterisk (*) denote variables significant at 1%, 5%, and 10%, respectively. Variables estimated as levels and then coefficients converted into elasticities with the exception of the dummy variables "Female head" and "Year", which are left as coefficients.

Table 4. Effects (Elasticities) of Multi-Year Lagged Median District Crop Productivity on Incomes (I) per Adult Equivalent (AE) – Log-Log with Multi-Year Moving Average (2016 ZMW)

	L.Total I/AE		L.Off-farm I/AE		L.Own-farm I/AE	
	Elasticity	*P*-value	Elasticity	*P*-value	Elasticity	*P*-value
Log district median	0.214***	0.000	0.116	0.185	0.254***	0.000
Adult equivalents	-0.786***	0.000	-0.785***	0.000	-0.733***	0.000
Education of the HH head	0.115**	0.010	0.181***	0.009	0.076	0.114
Female head (=1) (coef.)	-0.208**	0.014	-0.068	0.593	-0.214**	0.011
Landholding size (ha)	0.023***	0.002	0.008	0.351	0.030***	0.003
Tropical livestock units	0.060***	0.000	0.030**	0.032	0.077***	0.000
Value farm equipment	0.010**	0.042	0.009**	0.047	0.005	0.224
GS rainfall	0.498*	0.052	0.737*	0.070	0.547*	0.080
16 year mean rainfall	0.621	0.550	2.741*	0.081	0.807	0.608
Rainfall stress periods (SP)	-0.010	0.721	-0.081*	0.074	0.013	0.679
16 year mean rainfall SP	0.144	0.303	-0.083	0.694	0.178	0.311
16 year rainfall CV	0.178	0.486	0.386	0.333	-0.257	0.367
Cell phone density	0.116	0.349	0.157	0.337	0.113	0.369
Distance to district town	0.031	0.345	0.010	0.847	-0.003	0.919
Distance to paved road	0.026*	0.098	0.034	0.362	0.024	0.295
Distance to feeder road	0.002	0.421	0.007	0.187	0.000	0.966
Distance to market	-0.010	0.438	-0.051**	0.021	0.011	0.420
Distance to agro-dealer	-0.002	0.923	0.008	0.826	-0.011	0.558
Year (2015 = 1) (coef.)	0.146	0.155	0.494***	0.001	-0.241**	0.033

Note: There are 14,464 observations in the total income model, 14,324 observations in the off-farm income model, and 14,252 observations in the own-farm income model. Province dummies and province*year interaction effects included in all of the models, but not reported. Household time-averages of control variables included for CRE but not reported. Triple asterisk (***), double asterisk (**), and single asterisk (*) denote variables significant at 1%, 5%, and 10%, respectively. Control variables estimated as levels and then coefficients converted into elasticities with the exception of the dummy variables "Female head" and Year, which are left as coefficients

First, based on the lagged multi-year results, median crop productivity is a positive driver of total household income/AE in one of the two specifications (the log-log model in Table 4, but not the level-level model in Table 3). The log-log model (with an elasticity of 0.214) suggests that a doubling of lagged district-level median lagged crop productivity leads to a 21.4% increase in total household income/AE. Second, as we would expect, increases in lagged median district-level crop productivity drives subsequent increases in household-level own-farm income/AE, with an elasticity of 0.326 in the level-level Almon lag model (Table 3), and an elasticity of 0.254 in the log-log moving average model (Table 4). Third, as discussed above, according to the Johnston and Mellor (1961) hypothesis, we would expect there to be a positive multiplier effect of an increase in agricultural productivity on the off-farm economy. However, we do not find evidence of this; neither the level-level result nor the log-log results are significant.

In Table 5, we re-report the results from Tables 3-4, respectively, and also report the condensed results from similar models but where the median district-level crop productivity variables have been replaced with either the 10th and 90th percentiles of district-level crop productivity, or the mean productivity. As robustness checks to the log-log moving average specifications for each of these models, we also include the results from a level-level moving average specification.

Increases in the 10th percentile of district level productivity is not a significant positive driver of income in any of the models and is actually a negative driver in the moving average own-farm models. In contrast, increases in the 90th percentile is positive and significant for several of the models. Focusing on the log-log results, we find that a doubling of productivity at the 90th percentile contributes to a 28% increase in total income/AE, and a 53.6% increase in own farm income. This indicates that it is the productivity increases over time among the most productive segment of the farm population that drive the growth of own-farm incomes within a given district, perhaps due to the multiplier effect of greater commercialization. However, only the own-farm income results are significant in the level-level Almon lag and moving average specifications. The mean and median results are mostly consistent with each other in sign and significance level but the magnitude of the effects is generally greater for the mean than the median.

Table 5. Effects (Elasticities) of Lagged Multi-Year District Crop Productivity (Median, Mean, and 10th and 90th Percentile) on Household Incomes (I) per Adult Equivalent (AE) (2016 ZMW)

	Level-level: long-run				Log-log: long-run	
	Almon lag		Moving average		Moving average	
Total I/AE	Elasticity.	*P*-value	Elasticity	*P*-value	Elasticity	*P*-value
Median	0.139	0.261	0.187	0.171	0.214***	0.000
Mean	0.227	0.160	0.253	0.112	0.238***	0.000
10th percentile	0.012	0.934	0.214	0.408	-0.078	0.109
90th percentile	0.175	0.311	-.027	0.901	0.280***	0.000
Off-farm I/AE						
Median	0.018	0.927	0.124	0.576	0.116	0.185
Mean	0.003	0.991	0.106	0.657	0.044	0.619
10th percentile	0.132	0.598	0.410	0.375	0.017	0.844
90th percentile	-0.110	0.673	-0.308	0.415	0.021	0.840
Own-farm I/AE						
Median	0.326**	0.012	0.131	0.102	0.254***	0.000
Mean	0.470***	0.007	0.287**	0.022	0.383***	0.000
10th percentile	-0.163	0.196	-0.108**	0.030	-0.122**	0.034
90th percentile	0.673***	0.009	0.568***	0.004	0.536***	0.000

Note: There are 14,464 observations in total income models and level-level off farm income and own farm income models, 14,324 observations in log-log off-farm income models, and 14,252 observations in log-log own-farm models. Triple asterisk (***), double asterisk (**), and single asterisk (*) denote variables significant at 1%, 5%, and 10%, respectively. Variables estimated as levels and then coefficients converted into elasticities.

Next, in Table 6 we report the estimated lagged multi-year effects of an increase in district crop productivity for households with less than two hectares planted versus two or more hectares planted, respectively. Only the own-farm results are significant across most models. The off-farm results are only significant for the log-log models. The log-log results suggest that most of the positive impact from larger farm productivity on income applies specifically to own farm income, while the positive impact from smaller farm productivity applied specifically to off-farm income. A doubling of district-level median productivity on larger farms leads to a 49.4% increase in own farm income/AE, and a 31.4% decrease in off-farm income/AE. In contrast, a doubling of crop productivity on smaller farms has a negative effect on own farm income/AE, decreasing it by 21.7%, and a positive effect on off-farm income/AE, increasing it by 33.8%.

As mentioned in the data section, we tested each final regression model for attrition bias using the regression-based approach recommended by Wooldridge (2010). These results are reported in table A1 in the Appendix. For all of the level-level models (Almon and moving average), the null hypothesis of no attrition bias is never rejected. For the log-log moving average models, the null hypothesis is not rejected for the total income models, but it is rejected for the off-farm and own farm income models. As a robustness check, we re-estimated two of the models (median productivity on own-farm income, and median impact by land size category on off-farm income) in which the null hypothesis was rejected (i.e., where there was some evidence of attrition bias) using an inverse probability weighting approach.

Table 6. Effects (Elasticities) of Lagged Multi-Year Median District Crop Productivity on Total and Off-farm Income (I) per Adult Equivalent (AE) – Differentiated by Farm Size (2016 ZMW)

	Level-level: long-run				Log-log: long-run	
	Almon lag		Moving average		Moving average	
Total I/AE	Elasticity	*P*-value	Elasticity	*P*-value	Elasticity	*P*-value
Median: < 2 ha	0.397	0.307	0.438	0.335	0.016	0.868
Median: ≥ 2 ha	-0.229	0.542	-0.323	0.448	0.138	0.128
Off-farm I/AE						
Median: < 2 ha	0.828	0.223	0.990	0.220	0.338*	0.076
Median: ≥ 2 ha	-0.843	0.185	-1.02	0.167	-0.314*	0.058
Own-farm I/AE						
Median: < 2 ha	-0.149	0.179	-0.260**	0.012	-0.217*	0.071
Median: ≥ 2 ha	0.549***	0.006	0.560***	0.002	0.494***	0.000

Note: There are 2 districts where there were zero CFS observations of farms that cultivated >=2 hectares for at least one lag year, and so were dropped, corresponding to 184 observations. There are 14,280 observations in total income models and level-level models, 14,140 observations in off-farm log-log model, and 14,076 observations in own-farm log-log model. Individual lag years and control variables not reported. Household-level time-averages of control variables included for CRE but not reported. Triple asterisk (***), double asterisk (**), and single asterisk (*) denote variables significant at 1%, 5%, and 10%, respectively. Level-level model variables estimated as levels and then coefficients converted into elasticities.

We found that the results mostly told a similar story to the results presented above.[11] This gives us confidence that, overall, the core results presented above are robust.

As Table A1 shows, there is an interesting symmetry in the models where we find some evidence of attrition bias, potentially telling a story of the motivation of farm households to leave the farm or not. In the off-farm income log-log models, the coefficient is negative, around -0.12-0.13 suggesting that households represented in both waves of the panel have a lower off-farm income in the first wave, relative to households that dropped out of the second wave (by close to 12% in each model). We use the Kennedy (1981) approach for deriving the approximate percent change from the estimated coefficient of the dummy variable. In the own-farm income log-log models, the coefficient is positive, around 0.16-0.17, suggesting that households represented in both waves of the panel have a higher own-farm income in the first wave, relative to households that dropped out of the second wave (by around 18-19%, depending on the model). One possible reason for this is that farm households with greater off-farm sources of income have a higher opportunity cost of farming and are more likely to leave the farm. Conversely, households with greater own-farm sources of income may find it more worthwhile to stay on the farm.

Finally, we run a series of robustness checks. First, there is the possibility that some of the control variables might be affected by changes in lagged district-level crop productivity, causing us to under-estimate its impact on household income. We test for this by running the same set of models as in Tables 5 and 6, but we exclude all control variables that could plausibly be affected by changes in productivity, i.e., all except the rainfall control variables (see Tables A2 and A3 in the appendix).

In Table A2 we find very similar results as in Table 5 in terms of statistical significance and magnitude of impact, with the median and mean productivity impacts slightly higher, and the 90th percentile impacts slightly lower. In other words, there does not appear to be a significant under-estimate of productivity impact on income. Comparing Table A3 and Table 6, both of which differentiate by land size, we find minimal differences for the own-farm income models, but the log-log off-farm income models are no longer significant at the 10% level, and the log-log total income models becomes positive and significant for farms that cultivate more than two hectares.

Second, while most districts had plenty of observations in the CFS data of farms with >=2 hectares planted, there were anywhere from 1-11 districts each year that only had 1-9 observations. In the main results, we calculate district summary measures even when there are less than 10 observations. However, in Table A4, we run the same set of results, but exclude all districts that have less than 10 observations in any of the lag years – a total of 15 districts accounting for 1,918 observations. We find that the own-farm results do not change significantly, but the log-log off farm results are no longer significant at the 10% level. This indicates that the off-farm results should be interpreted with some caution.

[11] In the IPW off-farm model, the elasticities for the land size categories of <2 hectares and >=2 hectares are 33.4% and -30.2%, with p-values of 0.079 and 0.070, respectively. This is compared to the results above, 33.8% and -31.4%, with p-values of 0.076 and 0.058, respectively. In the IPW own-farm model, the elasticity is 26.5% and the p-value is 0.000. This is compared to the result above, 25.4% with a p-value is 0.000. In other words, there is very little change in both models.

Third, in the main set of log-log models, we leave all of the control variables in levels, while logging the relevant income and productivity variables. One of the reasons that we do this is because many of the control variables are either binary or have a significant number of zero values. However, as a robustness check, we log all of the control variables that do not have any zero values (including adult equivalents, growing season rainfall, long run average rainfall, the long run rainfall coefficient of variation, and district cell phone density) or have a relatively minimal amount (for household assets, when dropping both years if at least one year's observation had a zero value, results in a total of 144 dropped observations). The results in Table A5 show that the for most models, the direction and significance are the same, but magnitudes are higher, by a few percentage points in the median and mean models, and closer to 10% in the 90th percentile models. This suggests that our main set of log-log estimates are potentially a lower bound, and the magnitude of impact may be even higher.

However, as with the other robustness checks, the log-log off-farm land size models are no longer significant, indicating again to interpret them with caution.

6. CONCLUSIONS AND POLICY IMPLICATIONS

This study is one of the first to provide micro-level evidence from contemporary Sub-Saharan Africa on the extent to which agricultural productivity continues to be a key driver of broader economic development. Focusing on the case of Zambia, the study also estimates the extent to which lagged multi-year farm productivity influences household incomes through own farm vs. off-farm activities. In so doing, this work is a novel test of the Johnston-Mellor structural transformation model in a contemporary African setting using detailed household panel survey data. Our main findings are as follows, starting with the most robust.

Changes in district-level mean and median crop productivity have strong and positive lagged multi-year effects on the own-farm incomes of rural households in that district. We also find consistently strong impacts of productivity changes at the 90th percentile of households in the district, suggesting that it is the productivity changes among the most productive strata of farm households in the district that have the greatest indirect effects on the total and own-farm incomes of rural households.

Furthermore, it is the productivity in the relatively larger farms specifically that drives higher own farm income overall. This last result suggests that the relatively larger farms in our study may be reinvesting their productivity gains back on the farm and in improved marketing, and this may also be creating positive indirect multiplier effects on smaller farmers via improved input and output market access, and more favorable farmgate prices. These findings are consistent with Sitko, Burke, and Jayne (2018), who show that smallholders in Kenya and Zambia, especially in areas with a high concentration of relatively commercialized medium-scale farms, have greatly increased their sale of maize to large-scale traders in the last 10 years. This has resulted in these farmers receiving higher prices, along with improved access to private extension and input credit services.

Overall, the least robust set of results are between district-level crop productivity and off-farm household incomes, suggesting that some of the critiques of the multiplier effect hypothesis mentioned earlier for the African context may be valid (Elles 2005; Collier and Dercon 2014; Dercon and Gollin 2014). When not separating by land size, none of the results are significant. However, we do find tentative evidence (interpreted with caution due to their lack of significance in the robustness checks) that smaller farm productivity (<2 hectares) indirectly raises off-farm incomes. In other words, our overall results do not confirm the original hypothesis that an increase in agricultural productivity has multiplier effects on the rural off-farm economy - at least based on our sample of agricultural households - but productivity change among small farms in particular (<2 hectares planted) does at least in a couple of model runs. Smaller farmers may have a higher income elasticity of demand for locally-produced off-farm goods and services. Higher productivity creates surplus earnings and a market for rural off-farm economic activity, leading to more opportunities for local off-farm income generation, something that has shown to be of great importance to rural African household livelihood strategies in the last several decades (Reardon 1997; Barrett, Reardon, and Webb 2001; Haggblade, Hazell, and Reardon 2010; Dedehouanou et al. 2018).

There are some limitations to this study, mainly due to data limitations. First, it would have been useful to examine the relationship between agricultural *labor* productivity (not just agricultural *land* productivity) and the dependent variables of interest, but unfortunately this was not possible due to lack of sufficient labor use data in the Crop Forecast Surveys. Second, the scope of our productivity measures is limited to field crops for smallholder farmers in particular. The CFS data used in this study do not capture production of livestock, fruits, or vegetables, nor does the CFS include large-scale farms.

The findings of this study may help policymakers in Zambia prioritize rural economic investments. Overall, this study upholds the Johnston-Mellor structural transformation consensus that investments that raise agricultural productivity in a given district may raise the incomes of all rural farm households over the period of a few years. A doubling of district-level agricultural productivity is found to increase total incomes of households in the district by 21% and own-farm incomes of households in the district by 25% to 32% when summarizing by median productivity farms, and by even more so when the productivity increases emanate from higher productivity farms at the 90th percentile.

However, the effect of district-level agricultural productivity on the off-farm incomes of households in the district was less robust than we expected, although there is tentative evidence that increases in the agricultural productivity of local farms cultivating less than two hectares does increase the off-farm incomes of all households in the area.

While our research evaluated the impacts of crop productivity increases on sectoral income, a pathway for future research is to further explore the finding by Reardon (1997) that local off-farm wage income, as opposed to self-employment and migration earnings, is most important to rural household off-farm incomes. In particular, it would be useful to decompose sectoral income even more by breaking up off-farm income into off-farm wage income, off-farm business income, and remittances. It would also be useful to evaluate changes in sectoral composition as a result of farm productivity, e.g., movement of labor from own-farm to rural off-farm employment.

APPENDICES

Table A 1. Attrition Bias Test Results (Coefficients)

	Level-level: long-run				Log-log: long-run	
	Almon lag		Moving average		Moving average	
Total I/AE	Coef.	*P*-value	Coef.	*P*-value	Coef.	*P*-value
Median	-17.301	0.966	20.526	0.962	0.028	0.383
Mean	14.734	0.973	35.676	0.935	0.031	0.339
10^{th} and 90^{th} pct.	-47.076	0.906	-21.735	0.958	0.036	0.271
>2 ha, >=2 ha	-0.029	1.000	-17.480	0.966	0.030	0.360
Off-farm I/AE						
Median	-86.375	0.796	-57.630	0.872	-0.129**	0.013
Mean	-66.589	0.850	-49.137	0.892	-0.128**	0.014
10^{th} and 90^{th} pct.	-132.628	0.677	-108.330	0.739	-0.126**	0.016
>2 ha, >=2 ha	-94.452	0.786	-107.499	0.748	-0.130**	0.014
Own-farm I/AE						
Median	81.533	0.718	80.707	0.721	0.165***	0.000
Mean	83.706	0.710	84.230	0.710	0.170***	0.000
10^{th} and 90^{th} pct.	85.121	0.710	89.836	0.697	0.175***	0.000
>2 ha, >=2 ha	94.481	0.679	90.019	0.693	0.170***	0.000

Note: Coefficients represent the estimated coefficient on the dummy variable equal to 1 if the household in the first stage panel is also in the second stage.
Triple asterisk (***), double asterisk (**), and single asterisk (*) denote variables significant at 1%, 5%, and 10%, respectively.

Table A 2. Effects (Elasticities) of Lagged Multi-Year District Crop Productivity (Median, Mean, and 10th and 90th Percentile) on Household Incomes (I) per Adult Equivalent (AE) – Rainfall Controls Only (2016 ZMW)

	Level-level: long-run				Log-log: long-run	
	Almon lag		Moving average		Moving average	
Total I/AE	Elasticity.	*P*-value	Elasticity	*P*-value	Elasticity	*P*-value
Median	0.049	0.805	0.076	0.643	0.217***	0.001
Mean	0.191	0.320	0.199	0.277	0.264***	0.000
10th percentile	-0.032	0.823	0.201	0.456	-0.037	0.520
90th percentile	0.189	0.342	-.045	0.848	0.278***	0.000
Off-farm I/AE						
Median	-0.156	0.548	-0.073	0.783	0.090	0.364
Mean	-0.066	0.817	-0.002	0.993	0.056	0.582
10th percentile	0.030	0.903	0.377	0.429	0.029	0.746
90th percentile	-0.073	0.816	-0.323	0.426	0.040	0.739
Own-farm I/AE						
Median	0.342**	0.023	0.126	0.130	0.278***	0.000
Mean	0.500***	0.008	0.311**	0.019	0.417***	0.000
10th percentile	-0.059	0.592	-0.098*	0.071	-0.074	0.253
90th percentile	0.637**	0.012	0.559***	0.004	0.523***	0.000

Notes: There are 14,464 observations in total income models and level-level off farm income and own farm income models, 14,324 observations in log-log off-farm income models, and 14,252 observations in log-log own-farm models. 10th and 90th percentile included in the same model for each specification and income type; median and mean included in separate models for each specification and income type (27 total models). Individual lag years and control variables not reported. Household-level time-averages of control variables included for CRE but not reported.
Triple asterisk (***), double asterisk (**), and single asterisk (*) denote variables significant at 1%, 5%, and 10%, respectively. Level-level model variables estimated as levels and then coefficients converted into elasticities.

Table A 3. Effects (Elasticities) of Lagged Multi-Year Median District Crop Productivity on Total and Off-farm Income (I) per Adult Equivalent (AE) – Differentiated by Farm Size – Rainfall Controls Only (2016 ZMW)

	Level-level: long-run				Log-log: long-run	
	Almon lag		Moving average		Moving average	
Total I/AE	Elasticity	*P*-value	Elasticity	*P*-value	Elasticity	*P*-value
Median: < 2 ha	0.298	0.460	0.396	0.420	0.012	0.919
Median: ≥ 2 ha	-0.160	0.674	-0.282	0.532	0.194**	0.044
Off-farm I/AE						
Median: < 2 ha	0.621	0.377	0.903	0.297	0.264	0.193
Median: ≥ 2 ha	-0.704	0.280	-0.958	0.222	-0.209	0.219
Own-farm I/AE						
Median: < 2 ha	-0.111	0.337	-0.247**	0.023	-0.211	0.111
Median: ≥ 2 ha	0.527***	0.005	0.573***	0.002	0.505***	0.000

Notes: All but the rainfall controls are excluded. There are 2 districts where there were zero CFS observations of farms that cultivated >=2 hectares for at least one lag year, and so were dropped, corresponding to 184 observations. There are 14,280 observations in total income models and level-level models, 14,140 observations in off-farm log-log model, and 14,076 observations in own-farm log-log model. Each land size category estimated in the same model for each specification and income type (total of 9 models). Individual lag years and control variables not reported. Household-level time-averages of control variables included for CRE but not reported.
Triple asterisk (***), double asterisk (**), and single asterisk (*) denote variables significant at 1%, 5%, and 10%, respectively. Level-level model variables estimated as levels and then coefficients converted into elasticities.

Table A 4. Effects (Elasticities) of Lagged Multi-Year Median District Crop Productivity on Total and Off-farm Income (I) per Adult Equivalent (AE) – Differentiated by Farm Size – Stricter Criteria (2016 ZMW)

	Level-level: long-run				Log-log: long-run	
	Almon lag		Moving average		Moving average	
Total I/AE	Elasticity	*P*-value	Elasticity	*P*-value	Elasticity	*P*-value
Median: < 2 ha	0.359	0.270	0.497	0.253	0.006	0.959
Median: ≥ 2 ha	-0.128	0.653	-0.274	0.427	0.146	0.137
Off-farm I/AE						
Median: < 2 ha	0.777	0.173	1.091	0.163	0.225	0.330
Median: ≥ 2 ha	-0.700	0.125	-0.927	0.118	-0.235	0.219
Own-farm I/AE						
Median: < 2 ha	-0.154	0.111	-0.230	0.131	-0.197	0.212
Median: ≥ 2 ha	0.571**	0.018	0.526***	0.006	0.470***	0.001

Notes: In this robustness check, districts that have 1-9 CFS observations of >= 2 hectares cultivated in any of the lag years are dropped. This includes 15 (out of 72) districts and a total of 1,918 observations. There are 2 districts where there were zero CFS observations of farms that cultivated >=2 hectares for at least one lag year, and so were dropped, corresponding to 184 observations. There are 12,546 observations in total income models and level-level models, 12,416 observations in off-farm log-log model, and 12,368 observations in own-farm log-log model. Individual lag years and control variables not reported. Household-level time-averages of control variables included for CRE but not reported. Triple asterisk (***), double asterisk (**), and single asterisk (*) denote variables significant at 1%, 5%, and 10%, respectively. Level-level model variables estimated as levels and then coefficients converted into elasticities.

Table A 5. Effects (Elasticities) of Lagged Multi-Year District Crop Productivity (Median, Mean, and 10th and 90th Percentile) on Household Incomes (I) per Adult Equivalent (AE) – Log-Log with Multi-Year Moving Average – Selected Controls Logged (2016 ZMW)

	Log Total I/AE		Log Off-farm I/AE		Log Own-farm I/AE	
	Elasticity	*P*-value	Elasticity	*P*-value	Elasticity	*P*-value
Median	0.228***	0.000	0.114	0.185	0.284***	0.000
Mean	0.275***	0.000	0.063	0.471	0.427***	0.000
10th percentile	-0.154	0.000	-0.074	0.379	-0.164**	0.006
90th percentile	0.391***	0.000	0.122	0.226	0.629***	0.000
Median: < 2 ha	-0.015	0.864	0.273	0.139	-0.225*	0.066
Median: ≥ 2 ha	0.195	0.023	-0.245	0.125	0.533***	0.000

Notes: In this robustness check, continuous control variables that have relatively few if any zero values are logged (and if a household has zero values, they are dropped for both years to maintain a balanced panel), along with their CRE time averages. These logged control variables include adult equivalents, assets, growing season rainfall, long run average rainfall, and long run rainfall coefficient of variation, and district cell phone density. Of these only the total assets variables had zero values, and a total of 144 observations were dropped due to these. There are 2 districts where there were zero CFS observations of farms that cultivated >=2 hectares for at least one lag year, and so were dropped, corresponding to 184 observations. There are 14,320 and 14,136 observations in non-land and land size total income models, respectively; there are 14,182 and 13,998 in non-land and land size off-farm income models, respectively; and there are 14,118 and 13,942 observations in non-land and land size own-farm models, respectively. 10th and 90th percentile included in the same model for each income type; each land size category estimated in the same model for each income type; median and mean included in separate models for each income type. Individual control variables and their time averages not reported.

Triple asterisk (***), double asterisk (**), and single asterisk (*) denote variables significant at 1%, 5%, and 10%, respectively. Level-level model variables estimated as levels and then coefficients converted into elasticities.

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